Improving Climate Predictions through Ocean-data Assimilation

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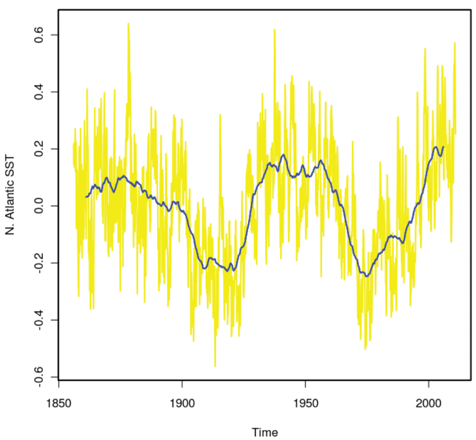
Real-world observations have to continually inform the increasingly sophisticated computational models of the climate system in order for the model trajectories to be related to the actual trajectory of the climate system (now routine in numerical weather prediction). A prerequisite for the successful combination of these two streams of information is a proper quantification of their respective uncertainties. An application of this procedure over the period for which observations are available is expected to improve climate predictions as well as help identify system sensitivities and modeling deficiencies.

Fig. 1. Area weighted average of the sea-surface temperature (SST) in the North Atlantic from 0 to 70 N using monthly Kaplan SST, and its 10-year running average–the AMO index [1]. The AMO affects air temperatures and precipitation over much of the Northern hemisphere, is associated with changes in the frequencies of North American droughts and severe Atlantic hurricanes, and renders the identification of anthropogenic climate change signals difficult. While links to oceanic thermohaline circulation have been hypothesized, the predictability of AMO is an area of active research. Nevertheless, proper initialization of the phase and amplitude of such large-scale features through the process of data assimilation is necessary to improve climate predictions.



On the interannual and longer time scales, ocean circulation mediates variability of the climate system because of its immense dynamical and thermodynamical inertia. Given such control of climate variability by ocean circulation, it is necessary that ocean models be initialized with conditions that represent as accurately as possible the actual ocean state, including the phase and amplitude of possible low-frequency oscillations (e.g., the Atlantic Multidecadal oscillation [AMO] in Fig. 1) in order to improve reliability of climate predictions.

However, global ocean circulation is a strongly coupled multiscale system with myriad physical processes occurring over a wide range of spatial and temporal scales that interact to give rise to complicated low-frequency variability. While there have been enormous advances in the understanding and modeling of global ocean circulation over the past half a century, an inescapable aspect of ocean circulation as regards prediction is the chaotic nature of the underlying dynamics. Consequently, the state of the modeled ocean circulation has to be continually reinitialized in order for the evolution of the modeled system to be related to that of the actual system. The periodic reinitialization is effected by the process of data assimilation wherein model forecasts and real-world observations are combined using their respective uncertainties.

We have recently developed an ensemble-based data assimilation system for the LANL ocean model POP (Parallel Ocean Program) using the Data Assimilation Research Testbed [2] of the National Center for Atmospheric Research (NCAR). In this approach, uncertainty of model-based prediction is quantified using an ensemble of model forecasts (highly computationally intensive). Notwithstanding the fact that such a method has the highly attractive feature of being able to better estimate uncertainty due to dynamic instabilities associated with the evolving flow, a frequent problem that plagues ensemble-based ocean data assimilation is that the RMS error grows faster than the ensemble spread.

As a consequence, the ensemble spread collapses all too soon leaving little room for the analysis step to make appropriate use of the available observations. In other words, the poor or collapsed ensemble spread is interpreted by the filter as high certainty in the model forecast, forcing it to neglect observations–in turn leading to increased root-mean-square (RMS) error–and an eventual failure of the assimilation. We have developed schemes to remedy such pathological divergence of model trajectories from observations by hybridizing dynamic ensemble-based estimates of uncertainty (which account for uncertainty due to those in initial conditions and those due to dynamic instabilities) with static estimates of uncertainty that account, in part, for model errors [3]. Successful assimilation of ocean observations was possible only with these improvements; the results of assimilating World Ocean Database observations over a 16-month period starting in 1990 in POP are shown in Figs. 2 and 3. The resulting improvement in prediction skill is shown in Fig. 4. In future work, we will use more recent ARGO float-based observations and develop hybrid schemes to enable assimilation of ocean observations in higher-resolution POP simulations than the one-degree resolution that we presently use.

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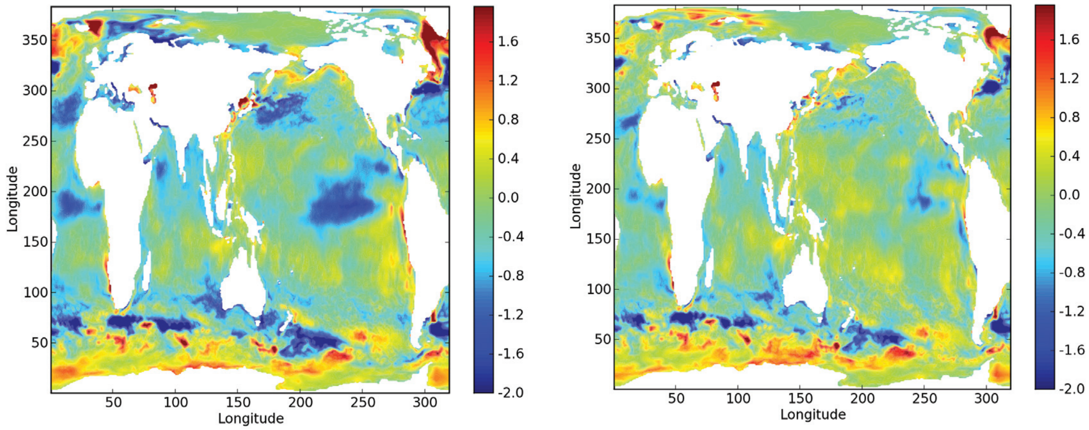

Fig. 2. Left: SST error of control ensemble run without assimilation. Error is with respect to NOAA OI SST v2 and is averaged over the 16-month period of the experiment. Note, cold bias in tropics and midlatitudes and warm bias at high latitudes and upwelling regions. Right: SST errors are reduced on successfully assimilating World Ocean Database observations. Note that NOAA OI SST v2 is not assimilated.

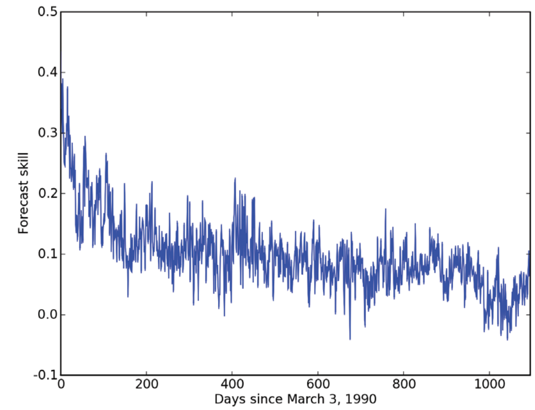

Fig. 4. Successful data assimilation improves skill over up to a year. Skill exhibits a fast decay over the first six months, followed by a slower decline.

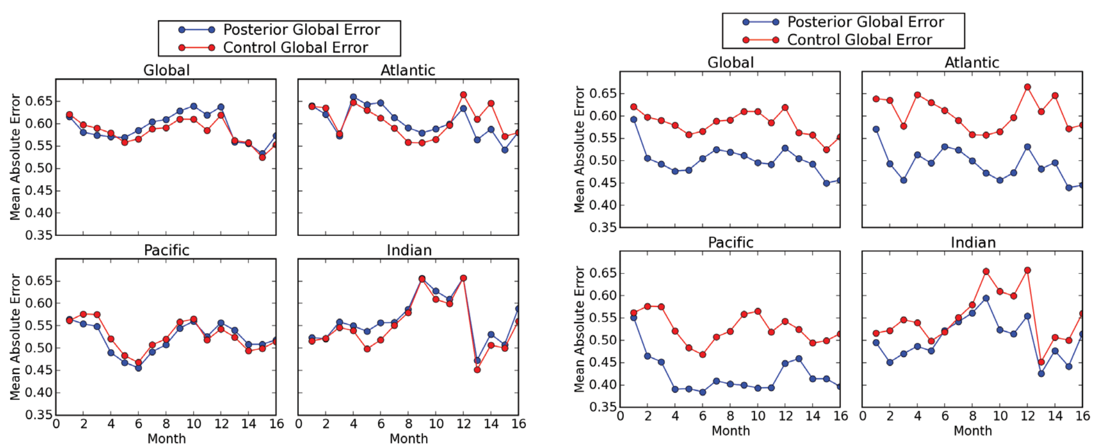

Fig. 3. Area-weighted mean absolute error of the monthly-averaged SST anomaly for January 1990 through April 1991. Left: A sophisticated statistical inferencing procedure fails to effect improvements over control in this assimilation experiment. Right: Hybridizing dynamic ensemble-based estimates of uncertainty with a static estimate leads to successful assimilation and significant reduction in error over control.

[1] Enfield, D.B. et al., *Geophys Res Lett* **28**, 2077 (2001).
[2] Anderson, J.L et al., *Bull Am Meteorol Soc* **90**, 1283 (2009).
[3] Nadiga, B.T. W.R. Capsper, and P.W. Jones, "*Ocean Data Assimilation: An Ensemble Data Assimilation System for the Parallel Ocean Program,*" Los Alamos National Lab. Technical Report LA-UR-12-10448

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